Int J Life Cycle Assess (2010) 15:994–1013
DOI 10.1007/s11367-010-0215-0

LIFE CYCLE IMPACT ASSESSMENT

Reducing bias through process inventory dataset normalization

Philip White · Mark Carty

Received: 17 November 2009 / Accepted: 21 June 2010 / Published online: 25 July 2010

Abstract
Purpose This paper explores a computational method to resolve some of the problems of external normalization in the life cycle impact assessment (LCIA) process of midpoint characterized impacts. Problems inherent to external normalization (per capita per year for a defined region) that reduce the ability to accurately calculate the most significant impact categories include

a) Bias created by a range of measurement disparities
b) Inverse proportion of the scale of the reference system impacts to the normalized product system impacts
c) Measurement and methodological uncertainties

Methods This paper demonstrates a method called Process Inventory Dataset (PID) normalization. PID normalization modifies the normalized impact value by a normalizing factor which puts a probability distribution on average normalized impact categories for an entire process inventory dataset.
Results PID normalization allows for significant variation of normalized impact ratio impact values among impact categories and among materials and processes. PID normalization works with incomplete process inventory and normalization data to deliver normalized impact ratio values that more accurately identify the impact categories with the most significant impacts in the LCIA process.
Conclusions Although PID normalization does not eliminate all of the bias that can occur from midpoint characterization and external normalization and may not reduce all uncertainties, it substantially trims the effects of normalization bias and eliminates inverse proportionality within one normalization dataset. It allows for a more accurate interpretation of normalized and weighted life cycle assessment results.

Keywords Bias · Inverse proportionality · LCIA · Normalization · Process Inventory Dataset (PID) normalization

1 Introduction

1.1 Normalization in life cycle assessment

In the life cycle assessment (LCA) process described by ISO 14044 (2006), Life Cycle Impact Assessment (LCIA) is the third required phase of the LCA process. LCIA provides "information to help assess a product system's Life Cycle Inventory results so as to better understand their environmental significance." ISO 14044 defines normalization as an optional calculation step in the LCIA phase. In LCA practice, normalization can be used for different reasons and can take several forms.

Norris (2001) notes two primary motivations for normalizing characterized indicator results. The first, operational motivation, converts attributes of product systems with dissimilar units into attributes with similar units. This process is sometimes performed prior to subsequent grouping or weighting steps that can assist in interpretation of LCA

Responsible editor: Michael Hauschild

P. White (✉)
School of Design Innovation and School of Sustainability,
Arizona State University,
Tempe, AZ 85287, USA
e-mail: p.white@asu.edu
e-mail: philip@orb-design.com

M. Carty
Department of Biological Statistics and Computational Biology,
Cornell University,
Ithaca, NY 14853, USA

results. The second motivation enables a contextual understanding of the relative magnitude for each indicator result of the product system. LCA practitioners increasingly use the contextual objective; this primary reason is allowed in the ISO 14044 definition for normalization in the LCIA phase (2006). ISO notes a third rationale for normalization, which is to perform consistency checks between substances accounted for in the reference product system and substances accounted for in the modeled product system. Inconsistencies between the two substance lists, or amounts of substances in the lists creates normalization data bias, a problem we will return to shortly.

Normalization is a calculation that divides an indicator result by a selected reference value. Two generic categories of normalization methods are common:

Internal normalization is the process where the characterized indicator results of a product system or service are divided by the characterized indicator results of an alternative product system, often with a similar system scale.

External normalization is the process where the characterized indicator results of a product system or service are divided by the characterized indicator results of a given area for a given period of time, often on a per capita basis.

Reap describes external normalization as a “comparison of the magnitude of the indicator results to information from some external reference system” (Reap et al. 2008). Distance-to-target weighting methods combine external normalization, usually on a regional basis, and weighting processes (Finnveden 1996; Seppäla and Hämäläinen 2001). This paper addresses external normalization values applied to characterized midpoint impact results with the application of weighting and does not apply to distance-to-target weighting methods that employ numerical targets and damage functions.

An array of potential problems in the external normalization process can reduce its effectiveness to accurately contextualize characterized impact results. The more common problems are bias, inverse proportionality, and various types of uncertainty. This paper describes a method that reduces bias and some types of inverse proportionality; it does not address concerns stemming from explicit or undefined uncertainties.

1.2 Normalization bias

Creators of impact category characterization factors may omit certain substances because the creators do not understand that particular substances should be accounted for, the creators may not know how to characterize the substances, or the creators may inaccurately model the characterization values. Likewise, collectors of process inventory data may lack the technical ability to or not have physical access to collect some types of substance emission data, the collectors may lack the knowledge that certain substance emissions should be accounted for, or the collectors may have made mistakes in their data collection process. Most profoundly, the creators of impact characterization methods are usually a different group of people than the collectors of process inventory data for specific processes. This disparity is further compounded by the reality that the collectors of process inventory data for specific processes are usually a different group of people than the estimators of external normalization values.

This array of potential problems creates normalization bias, when a quantitative disparity occurs between substances and impacts accounted for in the process inventory data and subsequent impact characterization (the numerator in the normalization fraction) and the substances accounted for and impacts characterized in the external normalization values (the denominator in the normalization fraction). Bias is especially problematic when the normalized impact results of different categories are compared for their contextual significance or to determine the quantify significance among the impact categories.

Heijungs et al. (2007) suggest that the best way to reduce normalization bias is to create process inventory databases and characterization factors “more completely, so that the risk of detrimental bias is reduced.” This is a rational and crucial objective, although it is doubtful that diverse teams of researchers collecting original process inventory data, creating impact characterization methods, and estimating normalization values will resolve these many problems quickly or easily. In the meanwhile, LCA practitioners need alternative methods to reduce or normalization bias.

We offer an example to demonstrate how normalization bias can occur. Eight hundred randomly selected materials and processes in the ecoinvent life cycle inventory (LCI) database were characterized with the TRACI characterization values (Bare et al. 2003) and normalized with year 2000 US per capita-year values (Bare et al. 2006). The normalized impact category divided by the total normalized impact for each material or process is measured, and the resulting averaged LCI impact category ratio of this dataset was calculated. Similarly, the same 800 materials and processes from the ecoinvent database were characterized with CML baseline 2001 and then normalized with global normalization values (also provided by CML) for the year 1995. The same LCI ratios were calculated for these characterization and normalization methods. Weighting values for these impact categories, which were created by the US National Institute for Standards and Technology (NIST) for Environmentally Preferable Purchasing (Gloria et al. 2007) and Building for Environmental and Economic Sustainability (BEES) software (Lippiatt 2007) are listed with impact category nomenclature clarifications (Table 1).

This comparison among the LCI dataset was evaluated with two characterization and normalization methods, and a set of weighting values is visualized in Fig. 1. The impact categories characterized by these two methods are based on entirely different models. If LCA practitioners use these

Table 1 Comparison of percent total impact of 800 ecoinvent processes characterized and normalized with two methods (LCI normalized impact ratios) and BEES 4.0 weighting values

Impact category	TRACI characterization with 2000 US normalization	CML 2001 baseline characterization with 1995 global normalization	BEES Environmentally Preferable Purchasing weights	Alternate nomenclature
Marine ecotoxicity	0%	57.9%	0%	
Fresh water ecotoxicity	0%	12.6%	0%	
Ozone layer depletion	0.1%	1.8%	2.5%	
Acidification	0.3%	4.5%%	3.6%	
Photochemical smog	0.2%	0.7%	4.2%	Photochemical oxidation in CML 2001
Terrestrial ecotoxicity	38.8%	3.2%	6.4%	Ecotoxicity in TRACI
Human toxicity	38.6%	1.5%	7.5%	Human health non-cancer in TRACI
Water eutrophication	0.2%	2.3%	9.0%	
Human carcinogens	21.2%	0%	9.2%	Human health cancer in TRACI
Human respiratory	0.1%	0%	10.7%	Human health criteria air in TRACI
Abiotic depletion	0.3%	11.4%	11.7%	Fossil fuel use in TRACI
Climate change	0.2%	5.5%	35.3%	Global warming in TRACI, CML 2001

Weighting values for the BEES categories which are not TRACI impact categories (indoor air quality, habitat alteration, and water intake) were deleted, and remaining values were apportioned to sum to a value of one

combinations of characterization and normalization methods and ecoinvent data, the results will be

- The TRACI 1.0 characterization and year 2000 US Normalization data focus almost exclusively on human toxicity, human cancer, and ecotoxicity.
- The CML Baseline 2001 characterization and year 1995 global normalization focus almost exclusively on marine toxicity, freshwater toxicity, and fossil fuel depletion.
- On the average, neither sets of characterization and normalization methods place a high value on global warming, which the BEES weighting attributes with

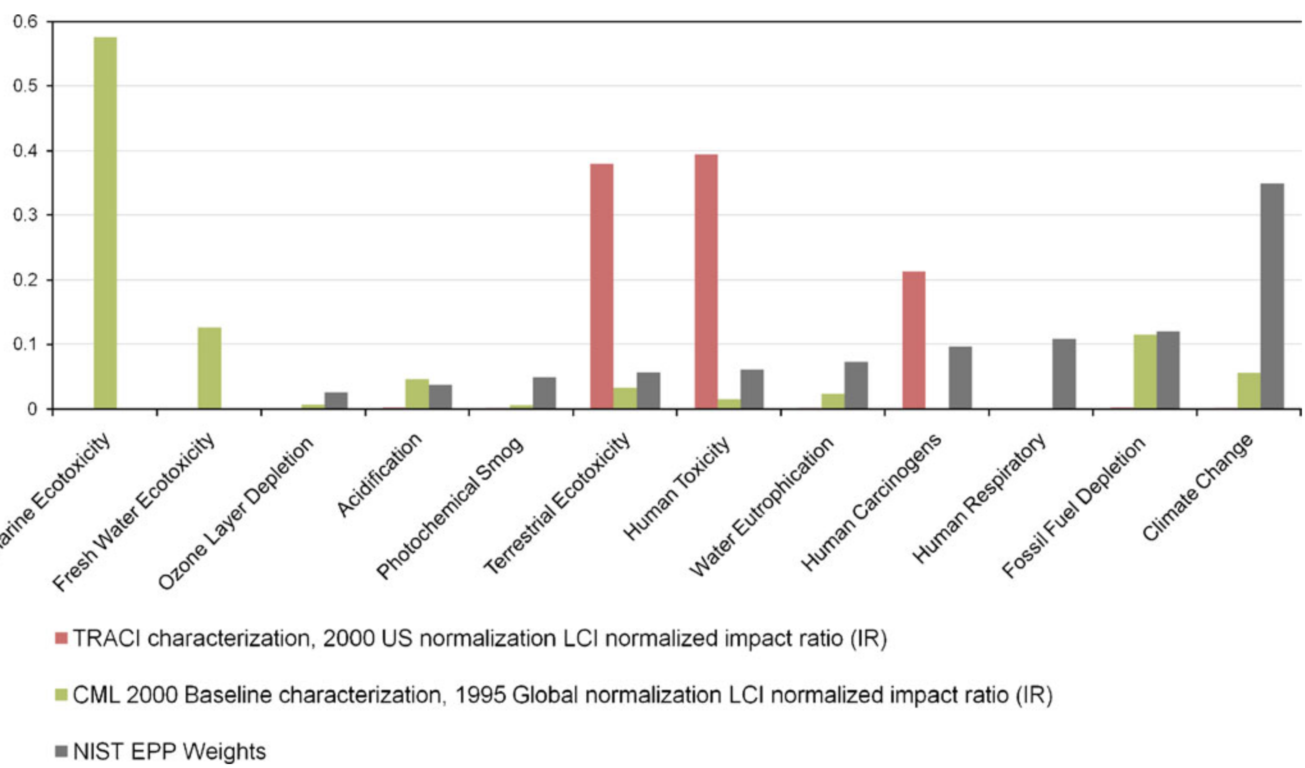

Fig. 1 Comparison of averaged characterization and normalization results on one set of LCI data and one weighting set, measured in percent total normalized impact

(and many concerned scientists argue has) a high priority.

Figure 1 illustrates that if LCA practitioners use characterized and normalized results in either of these combinations to ascertain the significance of the impacts as they are occurring between categories, there is a large disparity between the methods. Further, the results of these characterization and normalization methods deliver result ratios that diverge significantly from impact weights as presented in the BEES 4.0 weighting set. We consider this disparity to be an example of bias caused by a variety of dataset divergences. When different impact categories dominate the combined characterized and normalized impact results from different characterization and LCIA methods, as this example demonstrates, the objectivity of the LCIA process is brought into question. If some impact categories consistently dominate LCIA results and different sets of methods consistently deliver widely different LCIA results, LCA practitioners and recipients of LCA results are less likely to respect the accuracy of a result from any combination of characterization and LCIA methods.

1.3 Inverse proportionality in normalization

External normalization calculates the scale of impacts in inverse proportion to the scale of the reference system normalization value for each impact category. Impact categories with large annual per capita normalization values (such as climate change) deliver comparatively small normalized impact result values. Likewise, impact categories with small annual per capita normalization values (such as ozone layer depletion) deliver comparatively large normalized impact result values.

A simple example demonstrates inverse proportionality that can result from external normalization. Table 2 gives the characterized climate change value of a product and the climate change normalization values on a per capita basis for two groups. The high consumption group has an annual per capita climate change normalization value 100 times larger than the low consumption group.

Figure 2 visualizes the normalized results for individuals in the two groups. In this example, the product's normalized value is most appropriately interpreted as showing the

Table 2 Example characterized climate change product impact and per capita normalization values

Assessed product characterized climate change impact	1,000	kg CO_2 eq.
Per capita climate change normalization value, high consumption group	100,000	kg CO_2 eq./capita-year
Per capita climate change normalization value, low consumption group	1,000	kg CO_2 eq./capita-year

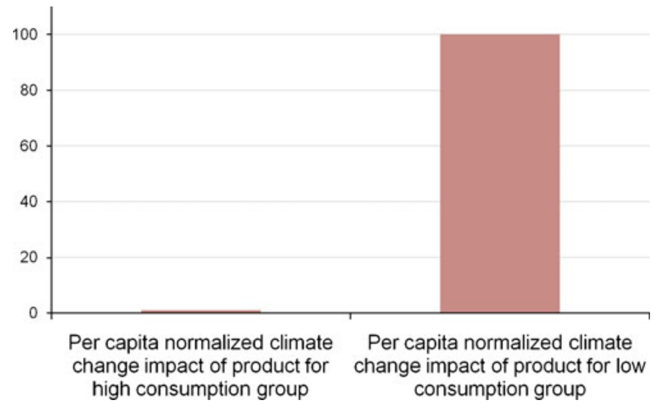

Fig. 2 Per capita externally normalized climate change impact of product in two groups

impact in proportion to the total impacts of a person per year. That is quite a different conclusion than interpreting that this indicates how important the impact category climate change is for this product. Clearly, the amount of climate change impact is identical in both products; it could be argued that in the group producing higher annual per person climate change emissions, climate change is a more serious problem. If the later method of interpretation is used, as is often the case, the inverse proportionality in external normalization confuses interpretation of the impact's relative significance and can lead to counterproductive actions.

Problems of inverse proportionality and bias in normalization support the argument for an additional computational or interpretive step (or steps) to clarify the importance and scale of the normalized impacts. A subsequent weighting step can be applied, as is allowed but not required by ISO 14044, to quantitatively prioritize the significance of normalized impacts among the impact categories. Such weighting values are often created independent of considerations of process inventory data values and characterization methods. Impact category weight values often do not adequately compensate for the severe differences in scale between the normalized results caused by various types of bias.

2 Methods

Process inventory dataset normalization We outline a method to attenuate many of the problems associated with external normalization bias. Life cycle process inventory dataset (PID) normalization employs the midpoint characterized and normalized values of an entire LCI database and performs an averaging process on the resulting normalized impacts in the LCI dataset. In this process, each impact category normalization value is divided by the ratio of the average normalized impact category value for the entire process inventory dataset to the sum of all normalized

Table 3 Materials and process sets for process inventory dataset normalization example (all data from ecoinvent, Switzerland 2007)

Quantity	Unit	Set
Set 1: homogeneous material (thermoplastics)		
6.9E−02	kg	Ethylene vinyl acetate (EVA)
2.9E−02	kg	Polystyrene, high impact (HIPS)
1.2E−01	kg	Polypropylene, granulate (PP)
1.3E+00	kg	Polymethyl methacrylate (PMMA)
3.6E+00	kg	Polystyrene, general purpose (GPPS)
4.4E+00	kg	Polyethylene, low density(LDPE)
7.4E+01	kg	Polyester 6
5.8E+02	kg	Polycarbonate
2.0E+00	kg	Polyethylene terephthalate (PET)
2.3E+00	kg	Polyethylene, high density (HDPE)
2.1E−02	kg	Polyvinylchloride (PVC)
Set 2: heterogeneous material or process		
6.9E−02	kg	Textile, woven cotton
2.9E−02	m^3	Concrete, exacting
1.2E−01	kg	Stainless steel, 18/8
1.3E+00	kg	Paper, bleached, from virgin wood
3.6E+00	kg	Polyethylene, high density (HDPE)
4.4E+00	kWh	Electricity, coal power plant
7.4E+01	km	Automobile, gasoline powered
5.8E+02	tonkm	Oceanic freight ship, diesel powered
2.0E+00	kg	Injection molding, for thermoplastic
2.3E+00	kg	Cardboard, in municipal incineration
2.1E−02	kg	Polyurethane, in sanitary landfill

impact categories values for the entire process inventory dataset. The calculation follows this sequence:

1. A large process inventory (LCI) data library is used in its totality, including all materials and processes. This can include many thousands of materials and processes.
2. Impacts of each material and process in the data set are individually characterized.
3. Impacts of each material and process in the data set are individually externally normalized on an annual per capita basis, to deliver the normalized impact ratios.
4. For each impact category, the LCI impact category ratio is calculated for the average normalized impact category value for the entire process inventory data divided by the sum of all normalized impact categories values for entire process inventory dataset.
5. The normalized impact ratio value is divided by the LCI impact category ratio to deliver the PID normalized value.
6. The PID normalized impact ratio value can then be multiplied by a weighting value.

Calculation methods similar to PID normalization are described in statistical literature (Bishop 2006; Lee 2002; Friely et al. 2003). For instance, Feller (1968) states that “a normalizing constant is a constant by which an everywhere non-negative function must be multiplied so the area under its graph is 1.” For discrete functions such as what we are using in PID normalization, the characterized and normalized impact categories should sum to a value of 1.

A formulaic description of PID normalization process follows.

Let G denote the collection of material or process systems. Let $X \in G$ denote the material or process system, the substances that comprise X are $\{X_j\}_{j=1}^{n}$, C_{ij} represents the midpoint characterization coefficient that links the system to the impact category j. We define the characterized result by

$$h_j(X) = \sum_{i=1}^{n} c_{ij} X_i$$

We denote $\dot{h}_j$ as the normalization factor for reference system category j. We use the symbol $\widetilde{h}_j(X)$ to represent the normalized category result ratio j of X, and so

$$\widetilde{h}_j(X) = \frac{h_j(X)}{\dot{h}_j}$$

Table 4 TRACI year 2000 US normalization values and units

Impact category	Normalization value	Equivalency unit
Ozone layer depletion	3.11E−01	kg CFC-11 eq./year-capita
Acidification	7.44E+03	moles H+ eq./year-capita
Photochemical smog	1.21E+02	kg NOx eq./year-capita
Human toxicity	1.47E+03	kg toluene eq./year-capita
Water eutrophication	1.80E+01	kg N eq./year-capita
Terrestrial ecotoxicity	7.38E+01	kg 2,4-D eq./year-capita
Human carcinogens	2.58E−01	kg benzene eq./year-capita
Human respiratory	7.63E+01	kg PM2.5 eq./year-capita
Abiotic depletion	3.70E+04	surplus megajoules/year-capita
Climate change	2.45E+04	kg CO_2 eq./year-capita

The PID normalization factor Z is defined by

$$Z = \sum_{j=1}^{m} \sum_{X \in G} \widetilde{h}_j(X)$$

Let f_j denote the fraction that category j represent as the sum of the characterized and normalized impact category result ratio, which is defined by

$$f_j = \frac{1}{Z} \sum_{X \in G} \widetilde{h}_j(X)$$

Let PID normalized result ratio $\overline{h}_j(X)$denote the average normalized impact category result ratio, which is defined by

$$\overline{h}_j(X) = \frac{\widetilde{h}_j(X)}{f_j}$$

Let w_j denote the weighting value for the impact category j. We define the PID weighted result ratio by

$$\widehat{h}_j(X) = w_j \overline{h}_j(X)$$

The scope of PID normalization in this paper was restricted to midpoint characterized impacts because normalization is more commonly employed in midpoint characterized LCIA. Further, some LCA practitioners consider that midpoint characterization has inherently higher certainty, in other words, delivers more robust results, than endpoint characterization. Bare et al. (2000) stated that “One major concern is that uncertainties (model, scenario and parameter) may be extremely high beyond well-characterized midpoints, resulting in a misleading sense of accuracy.” Bare and Gloria (2006) also noted that “there tends to be more consensus at (the midpoint) level of characterization when compared to the endpoint and damage calculations.” Finnvenden et al. (2006) noted that with midpoint methods, “there is no need to model the cause-effect chain all the way to the damage level, thus avoiding different types of uncertainties associated with such modeling. Furthermore, the question of discounting which is necessary in damage modeling and valuation is avoided.” Although there may be practical applications of PID normalization to damage assessment models and endpoint characterized LCIA, this paper explores the application of PID normalization on midpoint characterizes results.

Two sets of processes are used to demonstrate the PID normalization process. The homogeneous set, comprised of thermoplastic polymers from the ecoinvent database, was selected to demonstrate how PID normalization can be applied to similar processes. The heterogeneous set of processes, also from the ecoinvent database, was selected based on assumptions that these represent relatively common commodities used in high volumes in commerce and in diverse markets and products. By including a variety of processes in the second example, we intend to demonstrate how PID normalization can be uniformly applied to a variety processes with disparate impact profiles. Both sets of processes are listed in Table 3. We scaled the quantities of materials and processes to each deliver 1/11 of one point of normalized impact using the TRACI 1.0 characterization method and the year 2000 US normalization values.

The emissions created by the extraction and manufacturing of these materials, or the emissions created by the specific process, are characterized into discrete amounts of environmental impact categories measured in different equivalent units defined by the characterization methodologies. This example uses two combinations of midpoint characterization and normalization methods. The first set includes TRACI, a North American midpoint characterization method (Bare et al. 2003) that is normalized with external normalization values for the USA in the year 2000 (Bare et al. 2006). The values and units for these methods are listed in Table 4.

The second combined method includes CML Baseline 2001, a European midpoint characterization method normalized with global external normalized global values for the year 1995 (Guinée et al. 2002). The values and units for these methods are listed in Table 4. Marine water ecotoxicity and fresh water ecotoxicity, which are categories characterized in CML Baseline 2001, are omitted to enable consistency between the two methods.

3 Results

Data tables for Figs. 3, 4, 5, 6, 7, 8, 9, 10 are given in the Appendix.

The characterized and normalized impact ratios of the processes were calculated by dividing the characterized impacts by the external normalization values in Figs. 3 and 4. The TRACI characterized impacts is on the left of each bar pair, and the CML characterized values are on the right. Quantities of materials and processes were scaled to deliver 1/11 of one normalized TRACI impact point; the normalized CML impacts are readily seen as greater or less than these values.

Figure 3 indicates that the largest measured TRACI impact values for the homogeneous processes in this example are in the categories of human toxicity, human carcinogens, and terrestrial ecotoxicity. The anomalous high terrestrial ecotoxicity value of PVC can be traced back to dioxin emissions to air. Figure 3 also indicates that the largest measured CML baseline 2000 values can be attributed to abiotic depletion, climate change, and acid rain. None of the largest measured impact categories measured in one method are also measured in the other method.

Figure 4 indicates that the largest measured TRACI impact values for the heterogeneous processes in this

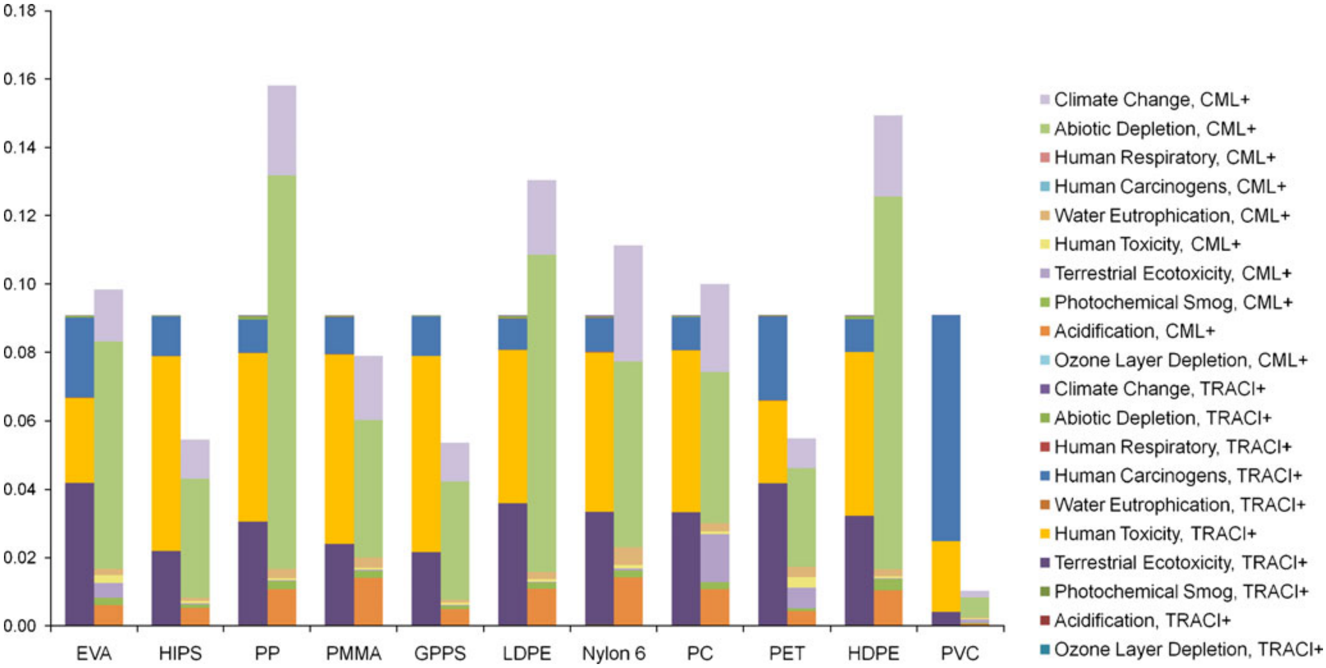

Fig. 3 Normalized impact ratios of homogeneous processes, stacked by process

example are in the categories of human toxicity, human carcinogens, and terrestrial ecotoxicity. These are the same largest scoring categories as in the homogeneous dataset. The large human toxicity value of polyurethane land-filling can be traced to lead emissions to water. Figure 3 also indicates that the largest measured CML baseline 2000 values can be attributed to abiotic depletion, climate change, terrestrial ecotoxicity, and acid rain. Terrestrial ecotoxicity is the only impact category that was measured to deliver a large percentage of the overall impact by both methods.

Figure 5 visualizes the same data as Fig. 3 with emphasis on the overall scale of the total impact per impact category

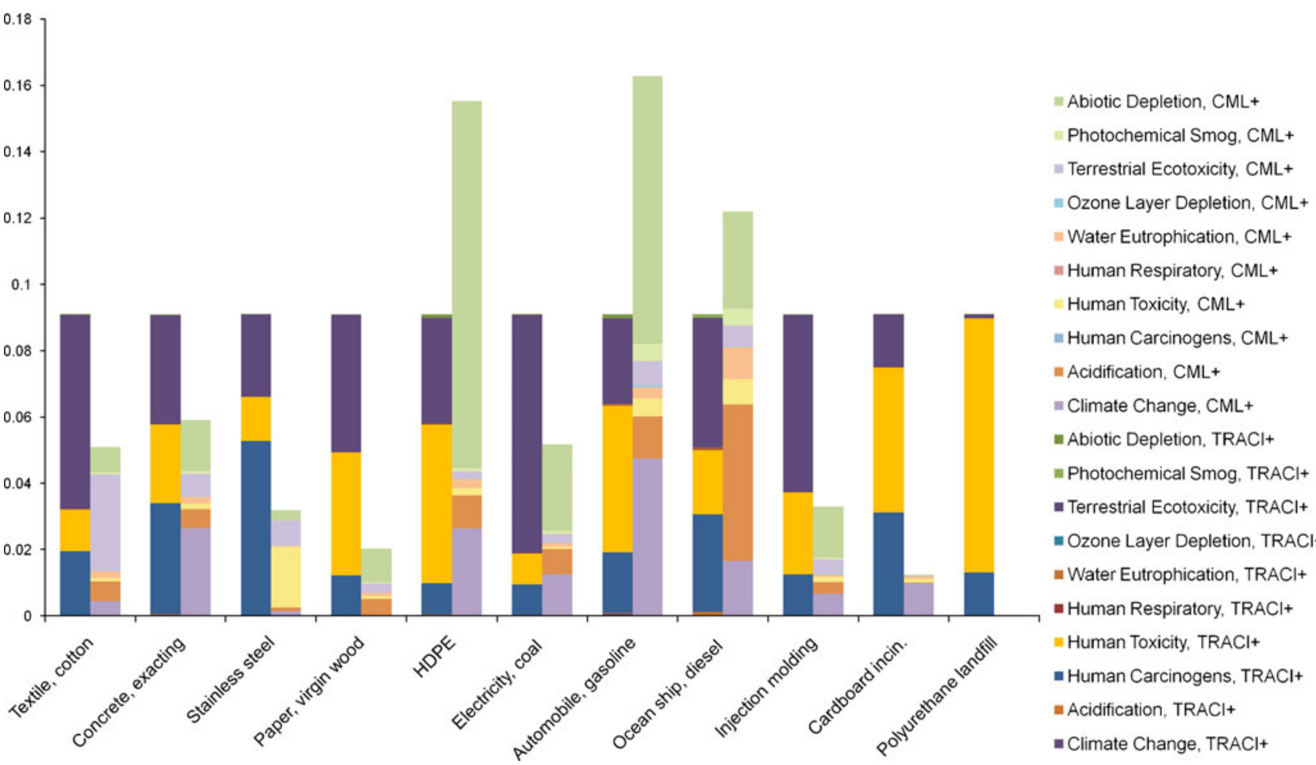

Fig. 4 Normalized impact ratios of heterogeneous processes, stacked by process

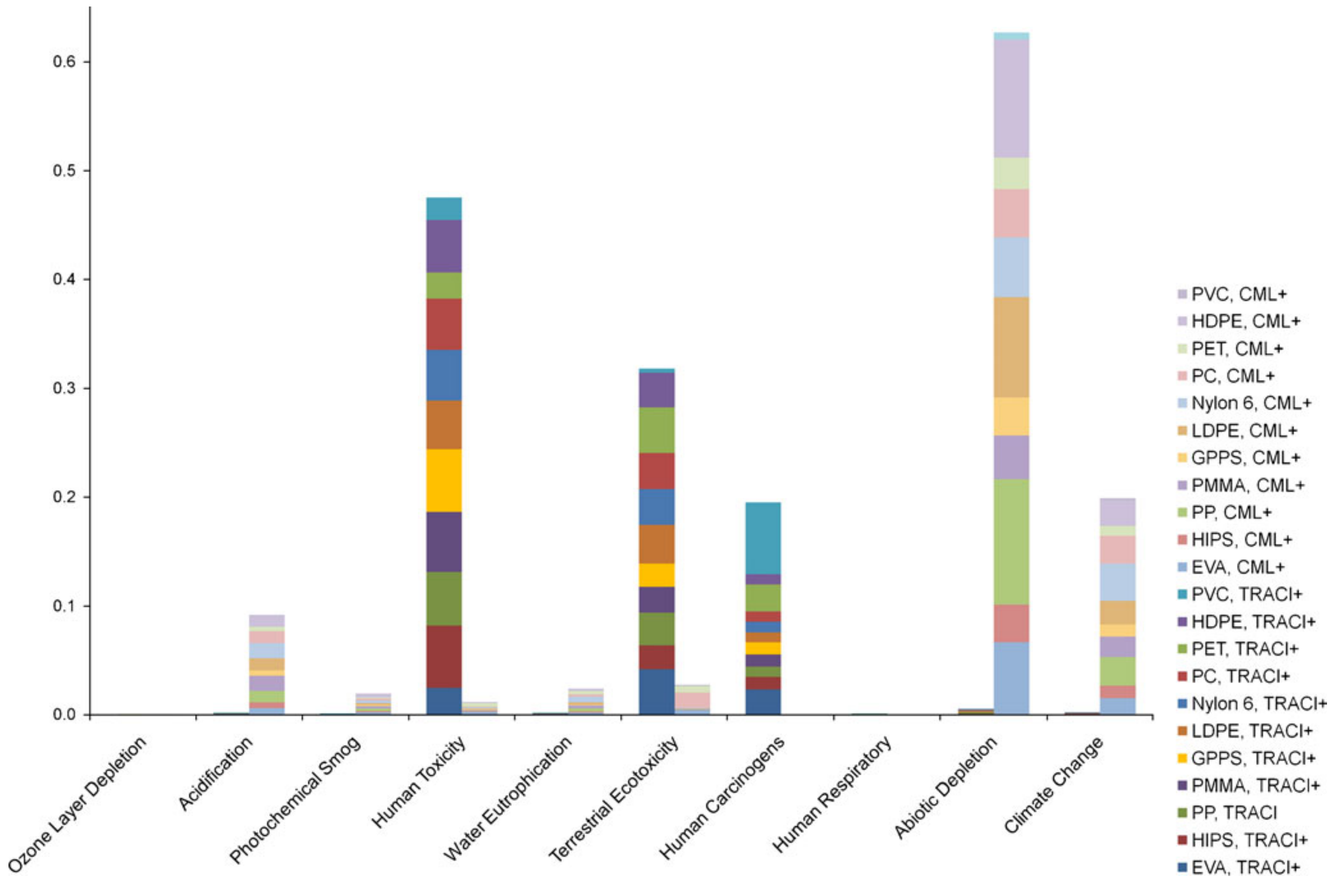

Fig. 5 Normalized impact ratios of homogeneous processes, stacked by impact category

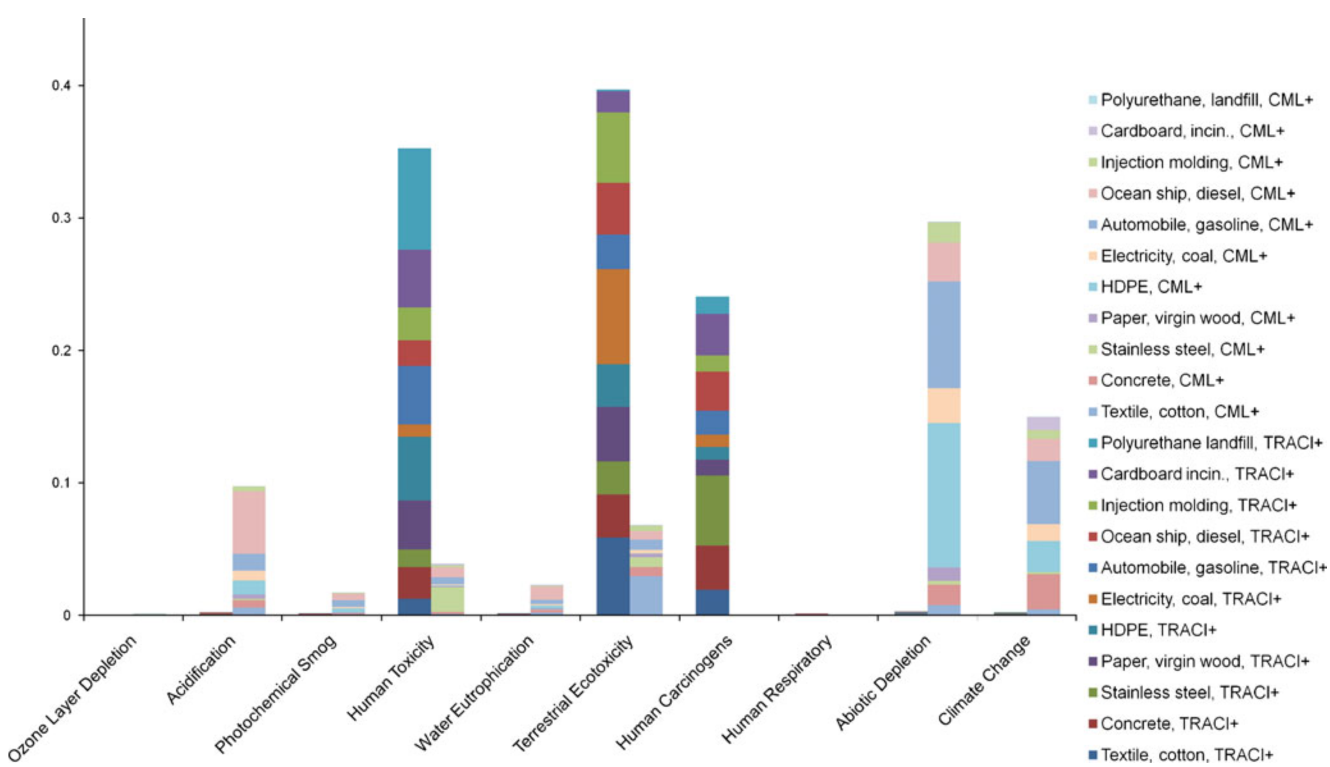

Fig. 6 Normalized impact ratios of heterogeneous processes, stacked by impact category

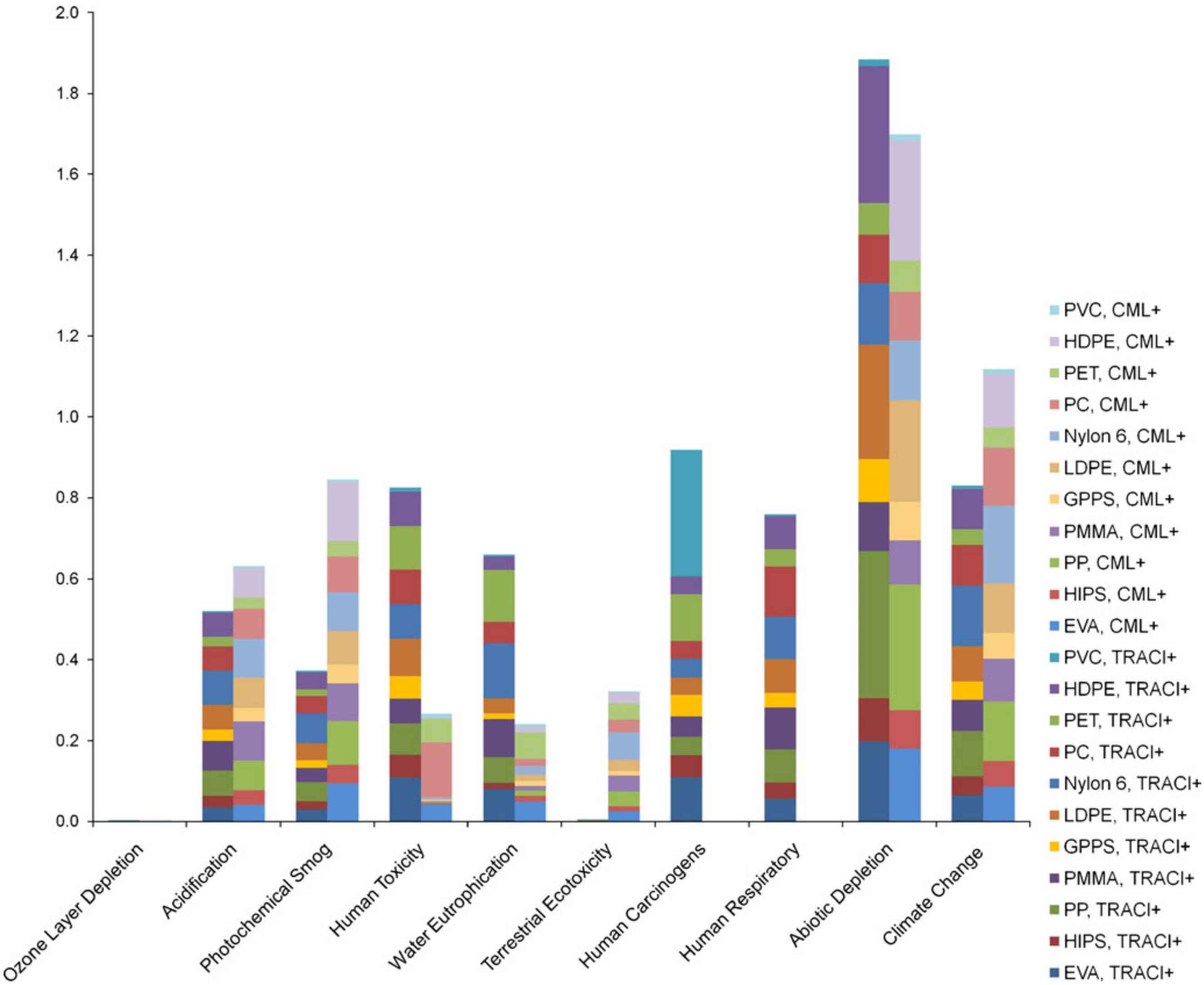

Fig. 7 PID Normalized impact ratios of homogeneous processes

of the homogeneous processes. Similarities to the averaged normalized impacts of the ecoinvent database as visualized in Fig. 1 are apparent. The largest total normalized TRACI impact categories are human toxicity, terrestrial toxicity, and human cancer; the largest normalized CML baseline 2000 impact categories are ozone depletion, abiotic depletion, and climate change (Table 5: CML 2002). The normalized values for ozone depletion in these and all subsequent graphs indicate the processes selected contributed little to ozone layer depletion processes.

Likewise, Fig. 6 visualizes the same data as Fig. 4 but emphasizes the overall scale of the total impact per impact category of the heterogeneous processes. For heterogeneous processes, we do not expect a large bias toward particular impact categories. However, the traditional method of midpoint characterization and normalization demonstrates a clear bias for particular categories, even when applied to heterogeneous processes. The largest measured impact categories are the same for both methods as in Fig. 5. The overall scale of the largest impact ratios for the heterogeneous processes is smaller than for the homogeneous processes because the greater diversity of emissions flows among the heterogeneous processes creates less concentrated impacts in the largest measured impact categories.

Steps 1 through 4 (in Section 2) were calculated for the 800 randomly selected materials and processes in the ecoinvent LCI database, with the two combinations of characterization and normalization methods. The normalized impact category result divided by the total normalized impact creates the LCI impact category ratio, as is described in step 4, and shown in Table 6.

This approach of normalizing the impacts to have a more uniform distribution is similar to what Seppäla and Hämäläinen (2001) states as the need to “convert the different scales of category indicator results into the same [0,1] range, which is an essential stage before weighting” (2001). Another way

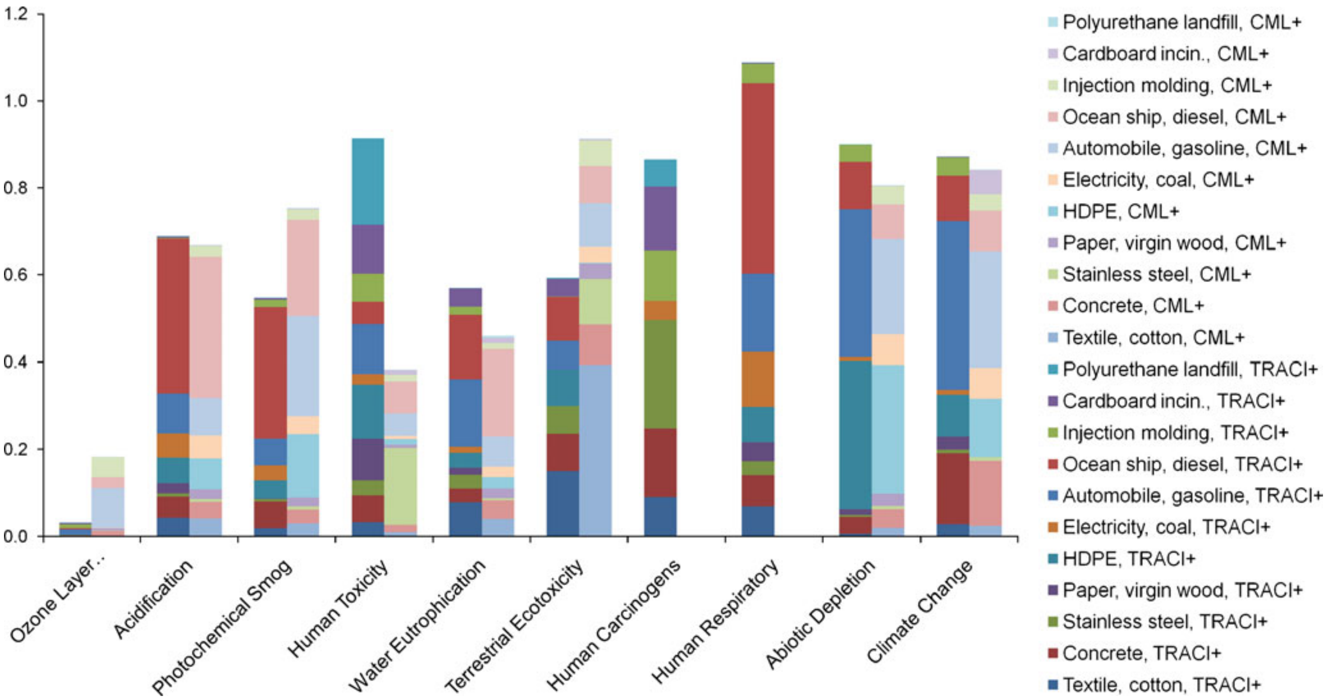

Fig. 8 PID Normalized impact ratios of heterogeneous processes

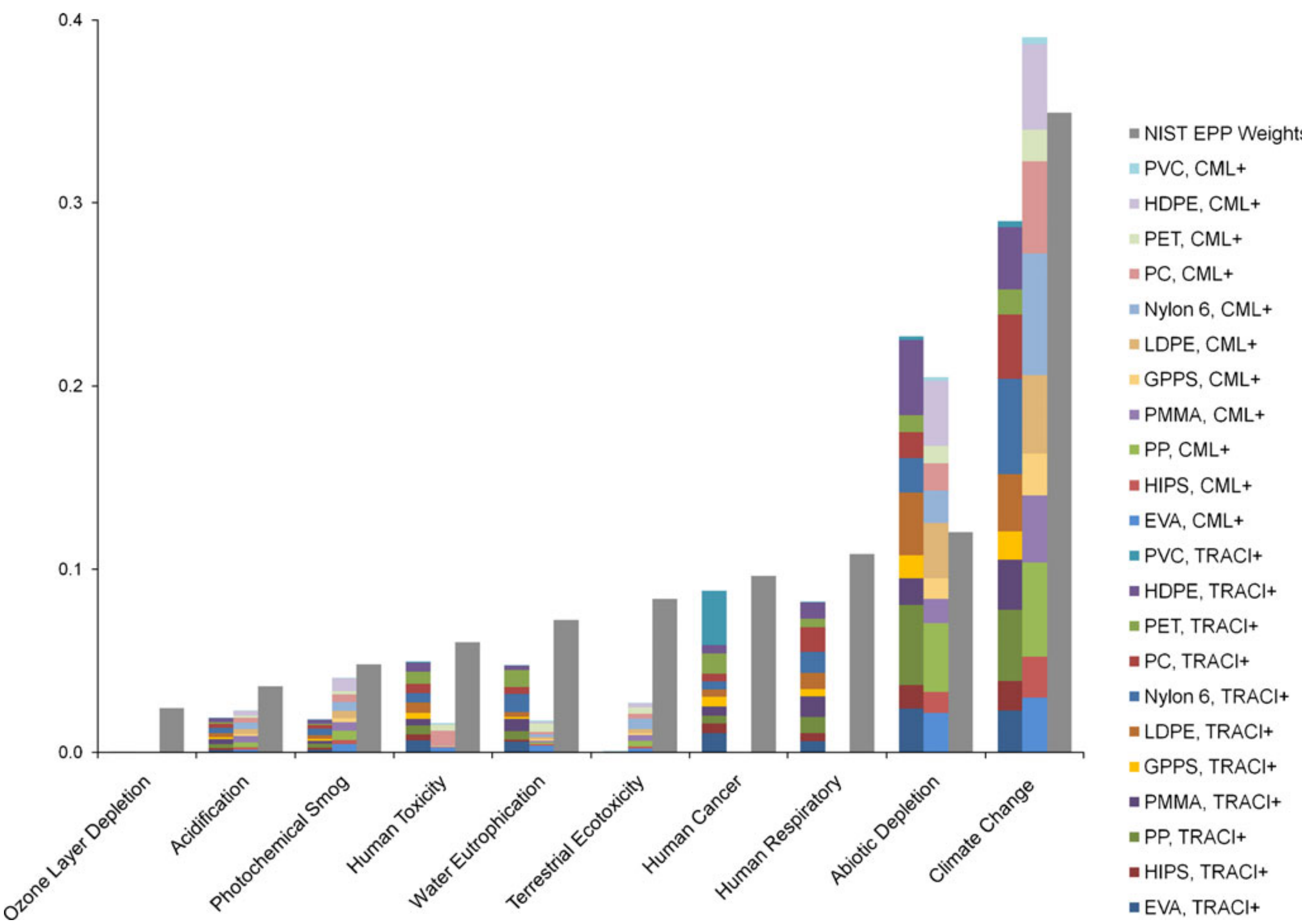

Fig. 9 PID normalized and weighted impact ratios of homogeneous processes and BEES weighting values

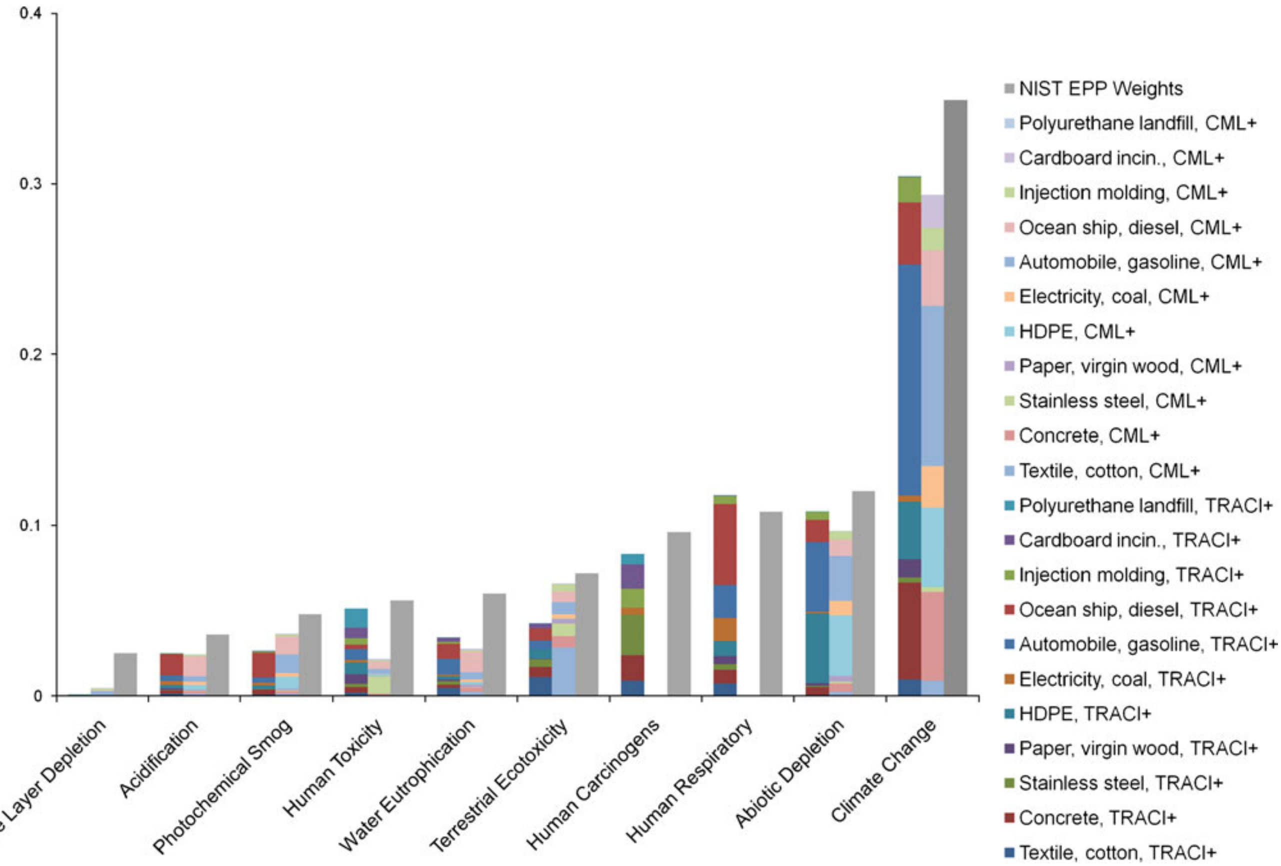

Fig. 10 PID normalized and weighted impact ratios of heterogeneous processes and BEES weighting values

of considering PID normalization is that if the average normalized impact ratio value of each impact category (assuming ten impact categories) were divided by the LCI impact category ratio, this would result in a net result value of 10% in each category. In other words, we have a uniform distribution; each impact category has, on the average, a similar value. Because we have a probability distribution, the sum of all the probabilities corresponding to each LCI impact category ratios must sum to one.

The normalized impact ratio is divided by the averaged LCI impact category ratio to deliver the PID normalized impact ratio value. The CML LCI ratios were adjusted (from those in Fig. 1) to exclude marine ecotoxicity and fresh water ecotoxicity categories which are not part of the TRACI weighting set. This allows the LCI normalized ratio values in each ratio set to sum to a value of one.

Figure 7 visualizes the PID normalized impact ratio values for the homogeneous processes, with the TRACI impacts on the left of each bar pair and the CML values on the right. The largest total PID normalized TRACI impact categories are now abiotic depletion, human carcinogens, and human toxicity; the largest total PID normalized CML baseline 2000 impact categories are abiotic depletion, climate change, and photochemical smog. Abiotic depletion

Table 5 CML Baseline 2001 and year 1995 global normalization values and units

Impact category	Normalization value	Equivalency unit
Ozone layer depletion	1.94E−09	kg CFC-11 eq./year-capita
Acidification	3.11E−12	kg SO_2 eq./year-capita
Photochemical smog	1.04E−11	kg C_2H_4 eq./year-capita
Human toxicity	1.75E−14	kg 1,4-DB eq./year-capita
Water eutrophication	7.56E−12	kg PO_4 eq./year-capita
Terrestrial ecotoxicity	3.72E−12	kg 1,4-DB eq./year-capita
Abiotic depletion	6.39E−12	kg Sb eq./year-capita
Climate change	2.41E−14	kg CO_2 eq./year-capita

Table 6 LCI normalized impact category ratios for TRACI with year 2000 US normalization and adjusted CML 2001 baseline with year 1995 global normalization

Impact category	TRACI characterization with 2000 US normalization	CML 2001 baseline characterization with 1995 global normalization (adjusted for TRACI impact categories)
Ozone layer depletion	0.1%	5.80%
Acidification	0.3%	14.6%%
Photochemical smog	0.2%	2.3%
Terrestrial ecotoxicity	38.8%	7.4%
Human toxicity	38.6%	10.4%
Water eutrophication	0.2%	4.9%
Human carcinogens	21.2%	0%
Human respiratory	0.1%	0%
Abiotic depletion	0.3%	36.9%
Climate change	0.2%	17.8%

was measured to have one of the largest PID normalized impacts by both methods on these homogeneous processes.

Figure 8 visualizes the PID normalized impact ratio values for the heterogeneous processes. The largest total PID normalized TRACI impact categories are human respiratory, abiotic depletion, and climate change. The increase in the PID normalized TRACI value for the human respiratory category compared to the normalized TRACI value is attributed to the relatively low PID normalization values for human respiratory impacts. The largest total PID normalized CML baseline 2000 impact categories are terrestrial ecotoxity, climate change, abiotic depletion, and acidification. Both methods share abiotic depletion, climate change, and acidification as having the largest PID normalized impacts.

We do not expect particular impact categories to dominate the assessed impacts of heterogeneous processes, and we would expect some correlation between results from different methods. Unlike the data in Fig. 6, PID normalized data for heterogeneous processes in Fig. 8 shows reduced bias toward particular impact categories. This demonstrates that PID normalization delivers more robust results than typical midpoint characterization and normalization methods.

After the PID normalization computation, a weighting step can be applied to indicate the socially defined importance of the various impact categories. We apply the NIST weighting values, as shown in Table 1, which were adjusted to reflect the impact categories represented in the TRACI characterization method. Figure 9 visualizes the PID normalized and weighted impact ratio values for the homogeneous processes, alongside the NIST weighting values in the left gray bar. Among these homogeneous processes, the largest measured PID normalized and weighted TRACI impact categories are clearly climate change and fossil fuel depletion. The largest measured PID normalized and weighted CML baseline 2000 impact categories are also climate change and fossil fuel depletion.

Similarly, Fig. 10 visualizes the PID normalized and weighted impact ratio values for the heterogeneous processes. The largest measured PID normalized and weighted TRACI impact category is clearly climate change. In a distant second place is human respiratory, which is somewhat dominated by diesel shipment, and abiotic depletion. The largest measured PID normalized and weighted CML baseline 2000 impact categories is also climate change, with terrestrial ecotoxicity and abiotic depletion measuring less impact.

Compared to Fig. 1, both Figs. 9 and 10 indicate that global warming is now the largest measured category for both the PID normalized and weighted TRACI and CML impacts. The scale of the PID normalized and weighted impact results correlate, on the average, more directly with the defined weighting values (in gray), for the selected materials and processes.

4 Discussion

In the two example sets of processes, there is still significant variation among the processes in the relative scale of impact categories that each process creates. Overall the scale of the PID normalized and weighted impacts more directly reflects the applied weighting value. This indicates that PID normalization with weighting can be applied to a wide variety of materials and processes with disparate impact profiles and characterization methods to deliver a result that more uniformly reflects the weighting values.

Process examples shown in Fig. 9 and 10 demonstrate that PID normalization with weighting makes the results of quite disparate midpoint characterization methods (CML baseline 2000 and TRACI, with different population normalizations) to deliver much more similar LCIA result values. The LCIA results of these different methods with PID normalization are not identical, but they are much more similar in scale and in proportion among the impact categories.

Ozone layer depletion is the most anomalous impact category in both example sets of processes. This demonstrates that the small number of materials and processes selected in both homogeneous and heterogeneous processes example did not create significant ozone layer depleting impact, on the average, compared to the entire process inventory dataset. The relatively high terrestrial ecotoxicity value calculated by PID normalized CML baseline 2000 impact ratio can be attributed to the heterogeneous materials selected in this example, which had a higher average impact than the entire process inventory database. Similarly, the relatively high abiotic depletion value for the homogeneous processes calculated by PID normalized and

weighted CML baseline 2000 impact ratio stems from the thermoplastics, which consume more fossil fuel than the average of the entire process inventory database.

The low ozone layer depletion results, the high terrestrial ecotoxicity impact results, and the high abiotic depletion results in the example demonstrate that PID normalization with weighting does not repress the variability in impact value that individual process inventory data create. These examples demonstrate that PID normalization can substantially reduce the acute differences among impact categories that often result from different characterization methods and normalization dataset combinations.

ISO 14044 prescribes that normalization is allowed in LCA practice; the standard recommends that the same characterized impacts be normalized with different reference systems to reveal changes that different reference systems create. PID normalization is implicitly allowed by ISO 14040 series standards if the PID normalization process is clearly described and documented.

Another approach to PID normalization would simply calculate the LCI normalized impact category ratios for those materials and processes that are part of the product system that is being modeled in the assessment. A problem with this approach is that the sample size will usually be much smaller than applying PID normalization of an entire dataset; thus, serious biases would often be created.

PID normalization values imply equal amounts of each material, and process in the dataset are produced (or consumed) in the region where the regular normalization values have been estimated. This is of course not the case and is the source of a type of PID normalization bias. This discrepancy, however, is obviously of a much smaller scale than the sizable bias that results from the combinations of process inventory data, characterization methods, and external normalization that prevail in much LCIA practice today.

PID normalization with weighting allows for considerable variation of normalized impact results on an impact category basis and among various materials and processes, while significantly reducing normalization bias in situations where it is impossible to deliver normalization and process inventory datasets with commensurate lists of substances. Further, PID normalization eliminates the effects of inverse proportionality among materials and processes that have been PID normalized with the same set of normalization values.

5 Conclusions

PID normalization reinforces the use of a weighting system and implies that a reasonable weight sets can be created. By reducing the variability of normalized results, PID normalization allows the weighting step to play a relatively larger role than usually occurs with non-PID normalization and weighting. The long-standing resistance to weighting by much of the scientific community is due largely to the non-scientific basis with which weighting values are created. However, compared to the sometimes dominant role that normalization bias can have on defining midpoint LCIA results, the combination of PID normalization with a weighting set that resulted from a deliberated consensus of environmental scientists (Soares et al. 2006), such as the NIST Environmentally Preferable Product weight set created by scientific panels, offers a logical alternative to common external normalization and weighting. In particular, NIST weighting places high emphasis on climate change, which concurs with the focus of much of the international scientific community (Finnveden et al. 2007).

To create LCI normalized impact ratios with the highest degree of quality and objectivity, the authors recommend that LCI normalized impact category ratios be calculated using the largest possible number of reference processes, preferably by teams of LCA practitioners and scientists working in peer review. Certainly, databases can be systematically analyzed (Ciroth 2009) to identify anomalies among these various data sets so the teams creating the datasets resolve the anomalies. As a routine practice, PID normalization values for standardized combinations of process inventory datasets, characterization methods, and external normalization values could consistently be made available in LCA computational software, making the PID normalization process easier to perform and more systematically applied.

PID normalization offers increased comparability and reliability of LCIA results among diverse midpoint characterization and normalization datasets and could lead to greater confidence among recipients of LCA studies (industries, regulators, and the public) in the accuracy and comparability of results from diverse midpoint characterization and LCIA methods. In lieu of the development of more consistently equalized process inventory datasets, characterization methods, and normalization datasets, PID normalization can reduce bias and allow LCA practitioners a logical method for interpreting the significance of midpoint environmental health, human health, and resource depletion impacts in the LCIA process.

PID normalization applied to midpoint assessments can be a method to reduce some, but not eliminate all, of the computational errors stemming from bias in midpoint characterized assessments. PID normalization in this research has been applied to midpoint characterization methods because there is generally more consensus about midpoint characterization methods than endpoint characterization methods. Whether PID normalization can significantly reduce potential bias that occurs in damage function or endpoint assessment methods is a topic that can be explored in future research.

Appendix

Table 7 Normalized impact ratio values of selected homogeneous processes (thermoplastics)

Material or process	Ozone depletion	Acidification	Photochemical smog	Terrestrial ecotoxicity	Human toxicity	Water eutrophication	Human carcinogens	Human respiratory	Abiotic depletion	Climate change
TRACI 1.0 impact characterization with year 2000 US normalization										
EVA	5.8E−07	9.5E−05	6.8E−05	4.2E−02	2.5E−02	1.8E−04	2.3E−02	4.7E−05	5.4E−04	1.6E−04
HIPS	3.5E−09	8.1E−05	4.6E−05	2.2E−02	5.7E−02	3.4E−05	1.1E−02	3.3E−05	2.9E−04	1.1E−04
PP	2.1E−09	1.7E−04	1.1E−04	3.0E−02	4.9E−02	1.5E−04	9.6E−03	6.8E−05	9.9E−04	2.7E−04
PMMA	1.6E−09	2.0E−04	7.9E−05	2.4E−02	5.5E−02	2.2E−04	1.1E−02	8.6E−05	3.3E−04	1.9E−04
GPPS	3.3E−09	7.6E−05	4.3E−05	2.1E−02	5.7E−02	3.3E−05	1.1E−02	3.1E−05	2.9E−04	1.1E−04
LDPE	2.6E−09	1.7E−04	9.6E−05	3.6E−02	4.5E−02	8.6E−05	9.0E−03	6.9E−05	7.7E−04	2.1E−04
Nylon 6	2.4E−09	2.3E−04	1.7E−04	3.3E−02	4.7E−02	3.2E−04	9.8E−03	8.8E−05	4.1E−04	3.5E−04
PC	2.3E−09	1.7E−04	9.7E−05	3.3E−02	4.7E−02	1.2E−04	9.5E−03	1.0E−04	3.2E−04	2.4E−04
PET	4.1E−07	6.6E−05	3.7E−05	4.2E−02	2.4E−02	3.0E−04	2.4E−02	3.6E−05	2.1E−04	9.4E−05
HDPE	2.3E−09	1.6E−04	9.6E−05	3.2E−02	4.8E−02	7.7E−05	9.5E−03	6.7E−05	9.2E−04	2.3E−04
PVC	2.6E−09	1.2E−05	9.8E−06	4.1E−03	2.1E−02	1.2E−05	6.6E−02	4.1E−06	4.5E−05	2.1E−05
CML baseline 2001 impact characterization with year 1995 global normalization										
EVA	4.6E−05	6.0E−03	2.1E−03	4.4E−03	2.4E−03	1.9E−03			6.7E−02	1.5E−02
HIPS	2.3E−07	5.2E−03	1.0E−03	3.1E−04	6.8E−04	9.2E−04			3.5E−02	1.1E−02
PP	1.8E−07	1.1E−02	2.4E−03	1.9E−04	6.0E−04	2.7E−03			1.2E−01	2.6E−02
PMMA	1.4E−07	1.4E−02	2.1E−03	3.4E−04	5.6E−04	2.9E−03			4.0E−02	1.9E−02
GPPS	2.2E−07	4.9E−03	1.1E−03	2.4E−04	6.0E−04	8.7E−04			3.5E−02	1.1E−02
LDPE	2.2E−07	1.1E−02	1.9E−03	2.7E−04	7.7E−04	2.1E−03			9.3E−02	2.2E−02
Nylon 6	2.1E−07	1.4E−02	2.2E−03	5.1E−04	1.1E−03	5.0E−03			5.5E−02	3.4E−02
PC	2.0E−07	1.1E−02	2.0E−03	1.4E−02	8.3E−04	2.4E−03			4.4E−02	2.6E−02
PET	3.2E−05	4.2E−03	8.8E−04	6.0E−03	3.1E−03	3.0E−03			2.9E−02	8.8E−03
HDPE	2.0E−07	1.0E−02	3.3E−03	2.2E−04	6.5E−04	2.0E−03			1.1E−01	2.4E−02
PVC	2.2E−07	6.7E−04	1.3E−04	1.0E−03	4.0E−04	2.3E−04			5.9E−03	1.9E−03

Table 8 Normalized impact ratio values of selected heterogeneous processes

Material or process	Ozone depletion	Acidification	Photochemical smog	Terrestrial ecotoxicity	Human toxicity	Water eutrophication	Human carcinogens	Human respiratory	Abiotic depletion	Climate change
TRACI 1.0 impact characterization with year 2000 US normalization										
Textile, cotton	1.1E−07	1.2E−04	4.4E−05	5.9E−02	1.3E−02	1.9E−04	2.0E−02	5.7E−05	1.7E−05	6.5E−05
Concrete, exacting	1.0E−06	1.3E−04	1.4E−04	3.3E−02	2.4E−02	7.4E−05	3.4E−02	6.0E−05	1.0E−04	3.9E−04
Stainless steel	1.0E−07	2.2E−05	1.2E−05	2.5E−02	1.3E−02	1.7E−05	5.2E−02	2.6E−05	1.3E−05	2.2E−05
Paper, virgin wood	4.6E−07	6.5E−05	4.0E−05	4.1E−02	3.7E−02	9.2E−05	1.2E−02	3.3E−05	7.1E−05	7.0E−05
HDPE	2.3E−09	1.6E−04	9.6E−05	3.2E−02	4.8E−02	7.7E−05	9.5E−03	6.8E−05	9.2E−04	2.3E−04
Electricity, coal	7.9E−08	1.5E−04	8.0E−05	7.2E−02	9.4E−03	3.4E−05	9.2E−03	1.1E−04	2.5E−05	1.7E−04
Auto., gasoline	7.9E−06	2.5E−04	1.4E−04	2.6E−02	4.5E−02	3.6E−04	1.9E−02	1.5E−04	9.2E−04	7.1E−04
Ocean ship, diesel	2.3E−06	9.8E−04	6.8E−04	3.9E−02	2.0E−02	3.4E−04	2.9E−02	3.6E−04	2.9E−04	2.5E−04
Injection molding	4.7E−06	6.9E−05	3.8E−05	5.3E−02	2.5E−02	4.3E−05	1.2E−02	1.1E−04	1.1E−04	1.0E−04
Cardboard incin.	1.5E−08	6.5E−06	8.4E−06	1.6E−02	4.4E−02	9.8E−05	3.2E−02	1.6E−06	1.7E−06	2.3E−06
PU landfill	2.1E−10	1.6E−08	2.0E−08	1.2E−03	7.6E−02	3.6E−05	1.3E−02	5.6E−09	2.2E−08	2.5E−08
CML baseline 2001 impact characterization with year 1995 global normalization										
Textile, cotton	7.1E−06	5.9E−03	6.8E−04	2.9E−02	1.0E−03	2.0E−03	0.0	0.0	7.6E−03	4.5E−03
Concrete, exacting	6.9E−05	6.1E−03	7.3E−04	7.0E−03	1.7E−03	2.1E−03	0.0	0.0	1.5E−02	2.6E−02
Stainless steel	6.1E−06	1.1E−03	1.6E−04	7.7E−03	1.9E−02	2.4E−04	0.0	0.0	2.9E−03	1.5E−03
Paper, virgin wood	2.8E−05	3.9E−03	4.6E−04	2.7E−03	7.7E−04	1.1E−03	0.0	0.0	1.0E−02	0.0E+00
HDPE	2.0E−07	1.0E−02	3.3E−03	2.2E−04	6.5E−04	2.0E−03	0.0	0.0	1.1E−01	2.4E−02
Electricity, coal	5.2E−06	7.6E−03	9.4E−04	2.7E−03	7.4E−04	1.2E−03	0.0	0.0	2.6E−02	1.2E−02
Auto., gasoline	5.3E−04	1.3E−02	5.2E−03	7.5E−03	5.3E−03	3.4E−03	0.0	0.0	8.1E−02	4.8E−02
Ocean ship, diesel	1.5E−04	4.7E−02	5.0E−03	6.3E−03	7.6E−03	9.7E−03	0.0	0.0	2.9E−02	1.6E−02
Injection molding	2.6E−04	3.5E−03	5.6E−04	4.4E−03	1.5E−03	6.5E−04	0.0	0.0	1.5E−02	6.8E−03
Cardboard incin.	9.7E−07	2.4E−04	2.9E−05	2.5E−04	1.1E−03	6.1E−04	0.0	0.0	2.5E−04	9.8E−03
PU landfill	1.4E−08	5.9E−07	4.1E−07	7.6E−06	2.3E−05	2.2E−04	0.0	0.0	2.1E−06	4.8E−06

Table 9 PID normalized impact ratio values selected homogeneous processes (thermoplastics)

Material or process	Ozone depletion	Acidification	Photochemical smog	Terrestrial ecotoxicity	Human toxicity	Water eutrophication	Human carcinogens	Human respiratory	Abiotic depletion	Climate change
TRACI 1.0 impact characterization with year 2000 US and PID normalization										
EVA	9.7E−04	3.5E−02	3.0E−02	1.1E−01	8.0E−02	4.8E−04	1.1E−01	5.6E−02	2.0E−01	6.6E−02
HIPS	5.8E−06	2.9E−02	2.0E−02	5.6E−02	1.5E−02	8.9E−05	5.4E−02	4.0E−02	1.1E−01	4.6E−02
PP	3.6E−04	6.2E−02	4.7E−02	7.8E−02	6.5E−02	3.9E−04	4.5E−02	8.2E−02	3.6E−01	1.1E−01
PMMA	2.7E−06	7.4E−02	3.5E−02	6.1E−02	9.4E−02	5.6E−04	5.0E−02	1.0E−01	1.2E−01	7.8E−02
GPPS	5.5E−06	2.7E−02	1.9E−02	5.5E−02	1.4E−02	8.4E−05	5.4E−02	3.7E−02	1.1E−01	4.5E−02
LDPE	4.3E−06	6.1E−02	4.3E−02	9.2E−02	3.7E−02	2.2E−04	4.3E−02	8.3E−02	2.8E−01	8.8E−02
Nylon 6	4.1E−06	8.4E−02	7.3E−02	8.6E−02	1.4E−01	8.1E−04	4.6E−02	1.1E−01	1.5E−01	1.5E−01
PC	3.8E−06	6.1E−02	4.3E−02	8.6E−02	5.3E−02	3.1E−04	4.5E−02	1.2E−01	1.2E−01	1.0E−01
PET	6.8E−04	2.4E−02	1.6E−02	1.1E−01	1.3E−01	7.6E−04	1.2E−01	4.4E−02	7.8E−02	3.9E−02
HDPE	3.8E−06	5.9E−02	4.2E−02	8.3E−02	3.3E−02	2.0E−04	4.5E−02	8.1E−02	3.4E−01	9.7E−02
PVC	4.3E−06	4.2E−03	4.3E−03	1.0E−02	5.2E−03	3.1E−05	3.1E−01	5.0E−03	1.7E−02	9.0E−03
CML baseline 2001 impact characterization with year 1995 global and PID normalization										
EVA	7.8E−04	4.1E−02	9.4E−02	4.2E−02	4.9E−02	2.5E−02			1.8E−01	8.5E−02
HIPS	4.0E−06	3.6E−02	4.6E−02	3.0E−03	1.4E−02	1.2E−02			9.4E−02	6.4E−02
PP	3.1E−06	7.4E−02	1.1E−01	1.8E−03	1.2E−02	3.7E−02			3.1E−01	1.5E−01
PMMA	2.4E−06	9.7E−02	9.3E−02	3.3E−03	1.2E−02	3.9E−02			1.1E−01	1.0E−01
GPPS	3.8E−06	3.4E−02	4.7E−02	2.4E−03	1.2E−02	1.2E−02			9.4E−02	6.4E−02
LDPE	3.8E−06	7.4E−02	8.4E−02	2.6E−03	1.6E−02	2.8E−02			2.5E−01	1.2E−01
Nylon 6	3.6E−06	9.7E−02	9.6E−02	4.9E−03	2.2E−02	6.8E−02			1.5E−01	1.9E−01
PC	3.4E−06	7.4E−02	8.7E−02	1.4E−01	1.7E−02	3.2E−02			1.2E−01	1.4E−01
PET	5.5E−04	2.9E−02	3.9E−02	5.8E−02	6.5E−02	4.0E−02			7.8E−02	5.0E−02
HDPE	3.4E−06	7.1E−02	1.5E−01	2.1E−03	1.3E−02	2.7E−02			3.0E−01	1.3E−01
PVC	3.8E−06	4.6E−03	5.8E−03	1.0E−02	8.3E−03	3.1E−03			1.6E−02	1.1E−02

Table 10 PID Normalized impact ratio values selected heterogeneous processes

Material or process	Ozone depletion	Acidification	Photochemical smog	Terrestrial ecotoxicity	Human toxicity	Water eutrophication	Human carcinogens	Human respiratory	Abiotic depletion	Climate change
TRACI 1.0 impact characterization with year 2000 US and PID normalization										
Textile, cotton	1.9E−04	4.3E−02	2.0E−02	1.5E−01	3.3E−02	7.9E−02	9.1E−02	6.9E−02	6.7E−03	2.7E−02
Concrete, exacting	1.7E−03	4.9E−02	6.1E−02	8.5E−02	6.1E−02	3.2E−02	1.5E−01	7.3E−02	3.8E−02	1.6E−01
Stainless steel	1.6E−04	7.9E−03	5.1E−03	6.4E−02	3.5E−02	3.3E−02	2.5E−01	3.2E−02	4.9E−03	9.1E−03
Paper, virgin wood	7.6E−04	2.4E−02	1.0E−03	2.4E−04	9.6E−02	1.5E−02	2.2E−06	4.4E−02	1.3E−02	2.9E−02
HDPE	3.8E−06	5.9E−02	4.3E−02	8.3E−02	1.2E−01	3.4E−02	1.1E−08	8.1E−02	3.4E−01	9.7E−02
Electricity, coal	1.3E−04	5.6E−02	3.5E−02	8.8E−05	2.4E−02	1.5E−02	4.4E−02	1.3E−01	9.2E−03	1.1E−02
Auto., gasoline	1.3E−02	9.2E−02	6.1E−02	6.7E−02	1.2E−01	1.5E−01	3.7E−05	1.7E−01	3.4E−01	3.8E−01
Ocean ship, diesel	3.7E−03	3.6E−01	3.1E−01	1.0E−01	5.0E−02	1.5E−01	1.1E−05	4.4E−01	1.1E−01	1.0E−01
Injection molding	7.9E−03	1.7E−03	1.6E−02	9.7E−05	6.4E−02	1.9E−02	1.2E−01	4.6E−02	3.9E−02	4.3E−02
Cardboard incin.	2.7E−03	2.4E−03	3.7E−03	4.0E−02	1.1E−01	4.3E−02	1.4E−01	2.0E−03	6.4E−04	7.3E−04
PU landfill	3.5E−07	6.1E−06	8.7E−06	2.9E−03	2.0E−01	2.4E−06	6.2E−02	6.8E−06	8.1E−06	9.2E−06
CML baseline 2001 impact characterization with year 1995 global and PID normalization										
Textile, cotton	1.2E−03	4.0E−02	2.9E−02	3.6E−01	9.9E−03	4.0E−02	0.0	0.0	2.1E−02	2.5E−02
Concrete, exacting	1.2E−02	3.8E−02	3.2E−02	9.3E−02	1.6E−02	4.3E−02	0.0	0.0	4.1E−02	1.5E−01
Stainless steel	1.1E−03	7.3E−03	7.2E−03	1.0E−01	1.7E−01	4.9E−03	0.0	0.0	8.0E−03	8.4E−03
Paper, virgin wood	4.9E−03	2.2E−02	2.0E−02	3.6E−02	7.4E−03	2.2E−02	0.0	0.0	2.7E−02	0.0
HDPE	3.4E−06	7.1E−02	1.5E−01	2.1E−03	1.3E−02	2.7E−02	0.0	0.0	3.0E−01	1.3E−01
Electricity, coal	9.1E−04	5.2E−02	4.1E−02	3.6E−02	7.2E−03	2.4E−02	0.0	0.0	7.1E−02	7.1E−02
Auto., gasoline	9.1E−02	8.7E−02	2.3E−01	1.0E−01	5.1E−02	6.9E−02	0.0	0.0	2.2E−01	2.7E−01
Ocean ship, diesel	2.6E−02	3.3E−01	2.2E−01	8.5E−02	7.4E−02	2.0E−01	0.0	0.0	8.0E−02	9.4E−02
Injection molding	4.6E−02	2.4E−02	2.5E−02	5.4E−02	1.5E−02	1.3E−02	0.0	0.0	4.1E−02	3.8E−02
Cardboard incin.	1.6E−04	1.6E−03	1.3E−03	3.3E−03	1.1E−02	1.2E−02	0.0	0.0	6.9E−04	5.6E−02
PU landfill	2.4E−06	4.0E−06	1.9E−05	1.0E−04	2.2E−04	4.6E−03	0.0	0.0	5.6E−06	2.7E−05

Table 11 PID weighted impact ratio values of selected homogeneous processes (thermoplastics)

Material or process	Ozone depletion	Acidification	Photochemical smog	Terrestrial ecotoxicity	Human toxicity	Water eutrophication	Human carcinogens	Human respiratory	Abiotic depletion	Climate change
TRACI 1.0 impact characterization with year 2000 US PID normalization and BEES EPP weighting										
EVA	2.3E−05	1.2E−03	1.5E−03	6.5E−03	5.8E−03	4.0E−05	1.1E−02	6.1E−03	2.4E−02	2.3E−02
HIPS	1.4E−07	1.1E−03	9.7E−04	3.4E−03	1.1E−03	7.5E−06	5.2E−03	4.3E−03	1.3E−02	1.6E−02
PP	8.6E−06	2.2E−03	2.3E−03	4.7E−03	4.7E−03	3.2E−05	4.4E−03	8.9E−03	4.4E−02	3.9E−02
PMMA	6.5E−08	2.7E−03	1.7E−03	3.7E−03	6.8E−03	4.7E−05	4.9E−03	1.1E−02	1.4E−02	2.7E−02
GPPS	1.3E−07	9.9E−04	9.2E−04	3.3E−03	1.0E−03	7.1E−06	5.2E−03	4.0E−03	1.3E−02	1.6E−02
LDPE	1.0E−07	2.2E−03	2.0E−03	5.6E−03	2.7E−03	1.9E−05	4.1E−03	9.0E−03	3.4E−02	3.1E−02
Nylon 6	9.8E−08	3.0E−03	3.5E−03	5.2E−03	9.9E−03	6.8E−05	4.4E−03	1.1E−02	1.8E−02	5.2E−02
PC	9.2E−08	2.2E−03	2.1E−03	5.2E−03	3.8E−03	2.6E−05	4.3E−03	1.3E−02	1.4E−02	3.5E−02
PET	1.6E−05	8.6E−04	7.9E−04	6.5E−03	9.3E−03	6.4E−05	1.1E−02	4.7E−03	9.5E−03	1.4E−02
HDPE	9.2E−08	2.1E−03	2.0E−03	5.0E−03	2.4E−03	1.7E−05	4.3E−03	8.8E−03	4.1E−02	3.4E−02
PVC	1.0E−07	1.5E−04	2.1E−04	6.3E−04	3.8E−04	2.6E−06	3.0E−02	5.4E−04	2.0E−03	3.1E−03
CML baseline 2001 impact characterization with year 1995 global PID normalization and BEES EPP weighting										
EVA	1.9E−05	1.5E−03	4.6E−03	2.5E−03	3.6E−03	2.1E−03			2.2E−02	3.0E−02
HIPS	9.7E−08	1.3E−03	2.2E−03	1.8E−04	1.0E−03	1.0E−03			1.1E−02	2.3E−02
PP	7.3E−08	2.7E−03	5.2E−03	1.1E−04	8.9E−04	3.1E−03			3.8E−02	5.2E−02
PMMA	5.8E−08	3.5E−03	4.5E−03	2.0E−04	8.4E−04	3.3E−03			1.3E−02	3.7E−02
GPPS	9.2E−08	1.2E−03	2.3E−03	1.4E−04	9.0E−04	9.8E−04			1.1E−02	2.2E−02
LDPE	9.1E−08	2.7E−03	4.0E−03	1.5E−04	1.1E−03	2.3E−03			3.0E−02	4.3E−02
Nylon 6	8.7E−08	3.5E−03	4.6E−03	3.0E−04	1.6E−03	5.7E−03			1.8E−02	6.6E−02
PC	8.1E−08	2.7E−03	4.2E−03	8.2E−03	1.2E−03	2.7E−03			1.4E−02	5.0E−02
PET	1.3E−05	1.0E−03	1.9E−03	3.5E−03	4.7E−03	3.3E−03			9.4E−03	1.7E−02
HDPE	8.2E−08	2.6E−03	7.0E−03	1.3E−04	9.7E−04	2.3E−03			3.6E−02	4.7E−02
PVC	9.2E−08	1.7E−04	2.8E−04	6.0E−04	6.0E−04	2.6E−04			1.9E−03	3.8E−03

Table 12 PID weighted impact ratio values of selected heterogeneous processes

Material or process	Ozone depletion	Acidification	Photochemical smog	Terrestrial ecotoxicity	Human toxicity	Water eutrophication	Human carcinogens	Human respiratory	Abiotic depletion	Climate change
TRACI 1.0 impact characterization with year 2000 US PID normalization and BEES EPP weighting										
Textile, cotton	4.4E−06	1.5E−03	8.1E−04	1.6E−02	2.2E−03	7.1E−03	8.4E−03	7.4E−03	7.8E−04	9.7E−03
Concrete, exacting	4.1E−05	1.8E−03	2.6E−03	8.9E−03	4.2E−03	2.9E−03	1.5E−02	7.8E−03	4.5E−03	5.8E−02
Stainless steel	4.0E−06	2.8E−04	2.2E−04	6.7E−03	2.4E−03	2.9E−03	2.3E−02	3.4E−03	4.5E−04	3.2E−03
Paper, virgin wood	1.8E−05	8.5E−04	4.4E−05	2.5E−05	6.6E−03	1.4E−03	2.0E−07	4.7E−03	1.6E−03	1.0E−02
HDPE	9.2E−08	2.1E−03	1.8E−03	8.7E−03	8.6E−03	3.0E−03	1.0E−09	8.7E−03	4.0E−02	3.4E−02
Electricity, coal	3.1E−06	2.0E−03	1.5E−03	9.3E−06	1.7E−03	1.3E−03	4.0E−03	1.4E−02	1.1E−03	3.7E−03
Auto., gasoline	3.2E−04	3.3E−03	2.6E−03	7.0E−03	7.9E−03	1.4E−02	3.4E−06	1.9E−02	4.0E−02	1.4E−01
Ocean ship, diesel	9.0E−05	1.3E−02	1.3E−02	1.1E−02	3.5E−03	1.3E−02	9.8E−07	4.7E−02	1.3E−02	3.7E−02
Injection molding	1.9E−04	6.2E−05	7.1E−04	1.0E−05	4.4E−03	1.6E−03	1.1E−02	4.9E−03	4.5E−03	1.5E−02
Cardboard incin.	6.5E−05	8.6E−05	1.6E−04	4.3E−03	7.8E−03	3.8E−03	1.4E−02	2.1E−04	7.6E−05	2.6E−04
PU landfill	8.5E−09	2.2E−07	3.7E−07	3.1E−04	1.4E−02	2.2E−07	5.7E−03	7.2E−07	9.5E−07	3.2E−06
CML baseline 2001 impact characterization with year 1995 global PID normalization and BEES EPP weighting										
Textile, cotton	3.1E−05	1.5E−03	1.3E−03	4.1E−03	6.8E−02	3.6E−03	0.0	0.0	2.4E−03	8.9E−03
Concrete, exacting	2.9E−04	1.4E−03	1.4E−03	9.8E−03	1.1E−02	3.9E−03	0.0	0.0	4.9E−03	5.3E−02
Stainless steel	2.6E−05	2.6E−04	3.1E−04	1.1E−02	1.2E−02	4.4E−04	0.0	0.0	9.3E−04	3.0E−03
Paper, virgin wood	1.2E−04	7.9E−04	8.5E−04	3.8E−03	5.1E−04	2.0E−03	0.0	0.0	3.2E−03	0.0
HDPE	8.2E−08	2.6E−03	7.0E−03	1.3E−04	9.7E−04	2.3E−03	0.0	0.0	3.6E−02	4.7E−02
Electricity, coal	2.3E−05	1.9E−03	1.8E−03	3.8E−03	4.9E−04	2.1E−03	0.0	0.0	8.5E−03	2.5E−02
Auto., gasoline	2.3E−03	3.1E−03	9.7E−03	1.1E−02	3.5E−03	6.2E−03	0.0	0.0	2.6E−02	9.4E−02
Ocean ship, diesel	6.5E−04	1.2E−02	9.4E−02	9.0E−02	5.1E−03	1.8E−03	0.0	0.0	9.3E−03	3.3E−02
Injection molding	1.1E−03	8.6E−04	1.0E−03	6.2E−04	1.0E−03	1.2E−03	0.0	0.0	4.9E−03	1.3E−02
Cardboard incin.	4.2E−06	5.9E−05	5.5E−05	3.5E−04	7.5E−04	1.1E−03	0.0	0.0	8.0E−05	2.0E−02
PU landfill	6.1E−08	1.5E−07	7.8E−07	1.1E−05	1.5E−05	4.1E−04	0.0	0.0	6.6E−07	9.6E−06

References

Bare J, Gloria T (2006) Critical analysis of the mathematical relationships and comprehensiveness of life cycle impact assessment approaches. Environ Sci Technol 40:1104–1113

Bare J, Gloria T, Norris G (2006) Development of the method and U.S. normalization database for life cycle impact assessment and sustainability metrics. Environ Sci Technol 40:5108–5115

Bare J, Hofstetter P, David W, Helias A, Udo de Haes H (2000) Midpoints versus endpoints: the sacrifices and benefits. Int J Life Cycle Assess 5(6):319–326

Bare J, Norris G, Pennington D, McKone T (2003) The tool for the reduction and assessment of chemical and other environmental impacts. J Ind Ecol 6:3–4

Bishop C (2006) Pattern recognition and machine learning. Springer, New York

Ciroth A (2009) Mathematical analysis of the ecoinvent database with the purpose of developing new validation tools. Life Cycle Assessment IX Conference http://lcacenter.org/LCA9/sessions/Databases.html. Accessed Oct 2009

Feller W (1968) An introduction to probability theory and its applications. Wiley, New York

Finnveden G (1996) Valuation methods within the framework of life cycle assessment. Swedish Environmental Research Institute, Stockholm

Finnveden G, Eldh P, Johansson J (2006) Weighting in LCA based on ecotaxes, development of a mid-point method and experiences from case studies. Int J Life Cycle Assess 11(1):81–88

Finnveden G, Hauschild M, Ekvall T, Guinée J, Heijungs R, Hellweg S, Koehler A, Pennington D, Suh S (2007) Recent developments in life cycle assessment. J Environ Manage 91:1–21

Friely N, Pettitt N, Reeves R, Wit E (2003) Bayesian inference in hidden Markov random fields for binary data defined on large lattices. J R Stat Soc 65(1):236–246

Gloria T, Lippiatt B, Cooper J (2007) Life cycle impact assessment weights to support environmentally preferable purchasing in the United States. Environ Sci Technol 41(21):7551–7557

Guinée J, Gorrée M, Heijungs R, Huppes G, Kleijn R, Wegener Sleeswijk A, Udo de Haes HA, de Bruijn J, van Duin R, Huijbregts M (2002) Handbook on life cycle assessment: operational guide to the ISO standards. Kluwer Academic Publishers, Dordrecht

Heijungs R, Guinée J, Klijn R, Rovers V (2007) Bias in normalisation: causes, consequences, detection and remedies. Int J Life Cycle Assess 12(4):211–216

Institute of Environmental Sciences (2002) Handbook on impact categories, CML 2001, Leiden University

International Organization for Standardization (2006) ISO 14044. Environmental management—life cycle assessment—requirements and guidelines, Geneva

Lee H (2002) Difficulties in estimating the normalizing constant of the posterior for a neural network. J Comput Graph Stat 11:222–235

Lippiatt B (2007) Building for environmental and economic sustainability technical manual and user guide 4.0. National Institute of Standards and Technology, Gaithersburg

Norris G (2001) The requirement for congruence in normalization. Int J Life Cycle Assess 6(2):85–88

Reap J, Roman F, Duncan S, Bras B (2008) A survey of unresolved problems in life cycle assessment. Part 2: impact assessment and interpretation. Int J Life Cycle Assess 13:374–388

Seppäla J, Hämäläinen R (2001) On the meaning of the distance-to-target weighting method and normalisation in life cycle impact assessment. Int J Life Cycle Assess 6(4):211–218

Soares S, Toffoletto L, Dechênes L (2006) Development of weighting factors in the context of LCIA. J Cleaner Prod 14:649–660